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# Infrared gait recognition based on wavelet transform and support vector machine

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ABSTRACT

To detect human body and remove noises from complex background, illumination variations and objects, the infrared thermal imaging was applied to collect gait video and an infrared thermal gait database was established in this paper. Multi-variables gait feature was extracted according to a novel method combining integral model and simplified model. Also the wavelet transform, invariant moments and skeleton theory were used to extract gait features. The support vector machine was employed to classify gaits. This proposed method was applied to the infrared gait database and achieved 78%–91% for the probability of correct recognition. The recognition rates were insensitive for the items of holding ball and loading package. However, there was significant influence for the item of wearing heavy coat. The infrared thermal imaging was potential for better description of human body moving within image sequences.

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## 1. Introduction

Biometric recognition refers to an automatic recognition of individuals based on feature derived from their anatomical and/or behavioral characteristics [1,2]. We can obtain the anatomical characteristics of the human beings by measuring their fingerprint, face, iris, hand shape and so on, and extract the behavioral characteristics from their behaviors, such as gait, voice and keystroke. Unlike conventional recognition techniques of passwords or ID cards, biometric recognition technique is safer and more reliable because it is almost impossible to be disguised, shared, and misplaced [3]. This makes biometric recognition much more difficult to be abused than traditional methods of identification.

Gait recognition, as one of new fields in biometric recognition, has unique capability to recognize people at a distance when other biometrics might not be perceivable. Furthermore, it is difficult to disguise gait without hampering progress, which is of particular interest in scene of crime analysis [4]. Gait can be detected and measured at low resolution, and therefore it can be used in situations where face or iris information is not available in high enough resolution for recognition [5]. However, there are a lot of challenges in gait recognition, such as foreground segmentation, clothing of the subject, walking speed change, carrying objects. In general, sensors of video collection include digital video (DV), professional camera and surveillance camera in gait recognition. It is difficult for these sensors to remove noises from complex background, illumination variation and carrying objects. Fig. 1 illustrates some influencing factors.

In order to improve the detection accuracy, we applied the technique of Infrared (IR) thermal imaging to recognize gaits. Human body is a natural emitter of infrared ray. Usually, the temperature of human body is different from that of background. This leads to the different energy distribution and gray-scale difference between background and human body in thermal image. Furthermore, if we use the technique of infrared thermal imaging, the environment will give little influence on the body detection. Especially, targets can be watched at night by using infrared thermal camera. Fig. 2 gives the comparison between conventional image and infrared image when subject walks with a package. The conventional images were taken outdoors in the afternoon. The outdoor lighting was very stable. Otherwise the complex environment would make the silhouette extraction more difficult. The package changes human body silhouette in the conventional image as shown in Fig. 2(b) and the impact from package is difficult to remove. However, Fig. 2(c) reveals that the package is invisible in infrared image because of different temperature between human body and the package. The clean silhouette can be generated for the infrared image as illustrated in Fig. 2(d). The infrared pattern facilitates silhouette extraction. So we collected infrared gait video with FLIR A40M thermal camera in our experiments. Daoliang Tan [6] used infrared camera to collect gait video at night. This technique is difficult to remove the influence from noises such as carrying object and illumination variations. Bhanu and Han [7,8] used FLIR SC2000 long-wave infrared thermal camera to deal with human activity recognition.

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Each subject was asked to walk slowly, walk fast and run forward and backward. There were five subjects to be tested in their experiments. However, they did not analyze the situation for carrying objects. For this reason, we used the IR thermal camera to collect gait video and established a database of Infrared Thermal Gait with 23 subjects. Each subject was asked to walk with four conditions: walking in a natural manner, holding ball, loading package and walking with heavy coat.

In addition, we used a novel method that the integral model was combined with the simplified model to obtain multi-variables gait features. The integral model is based on body silhouettes. By using this integral model, we can identify persons by analyzing motion information of silhouettes, such as walking speed, area change of silhouettes. The simplified model is based on the anatomic principles to simplify human body. But there is some limitation to extract gait feature by using single model (integral model or simplified model). The integral model based on silhouettes is excellent to recognize subjects fast and directly. But there is an indirect connection between the silhouette and the gait. Also complex background can influence the silhouette extraction. So the gait feature based on integral model is easy to be disturbed by background [9–11]. If we only use the simplified model to extract gait feature, some information (such as body width) will be lost after simplifying the human body. On the side, the gait feature generally includes behavioral characteristic or anatomical characteristic. How can we obtain the effective features including not only behavioral characteristic, but also anatomical characteristic? For this reason, this paper gives a novel method that integral model is combined with simplified model to obtain multi-variables information.

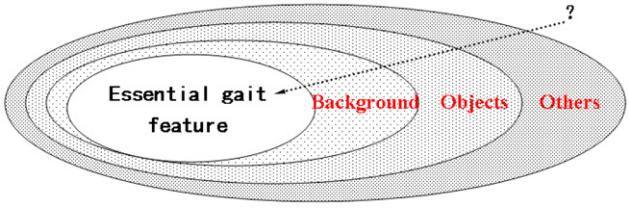


**Fig. 1.** Sketch map of influencing factors in gait recognition.

At the same time, the wavelet transform (WT) and invariant moments were used to extract gait parameters. Also the grey-level gait energy image (GEI) was simplified to obtain body skeleton and to extract gait parameters. The GEI [12–15] reflects major shapes of silhouettes and their changes over gait cycle. So we extracted human silhouettes from the infrared video and obtained the GEI in this paper. These gait parameters were fitted together and presented to support vector machine for classification. Fig. 3 illustrates the technical flow chart.

## 2. Methods

### 2.1. Infrared video collection

In our experiments, the infrared thermal camera A40M was used to collect gait video. This thermal camera is a tool for infrared detection technology. The kernel of camera is the infrared

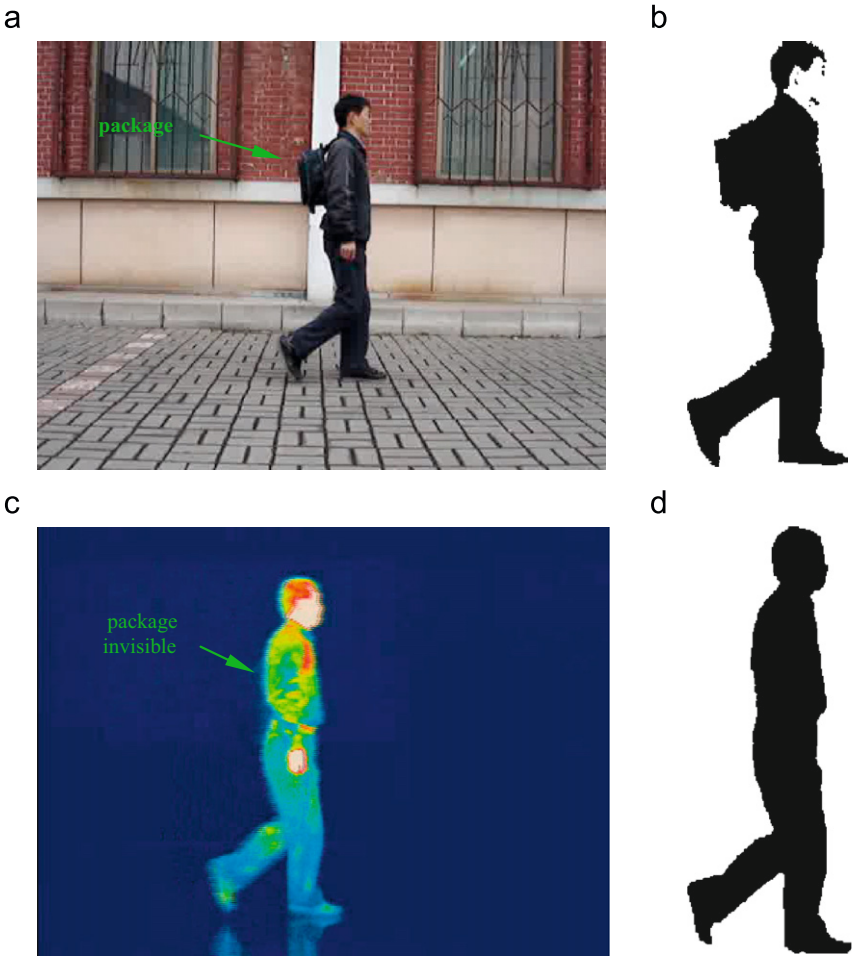


**Fig. 2.** Comparison of IR and conventional images: (a) conventional image, (b) silhouette in conventional image, (c) IR image and (d) silhouette in IR image.

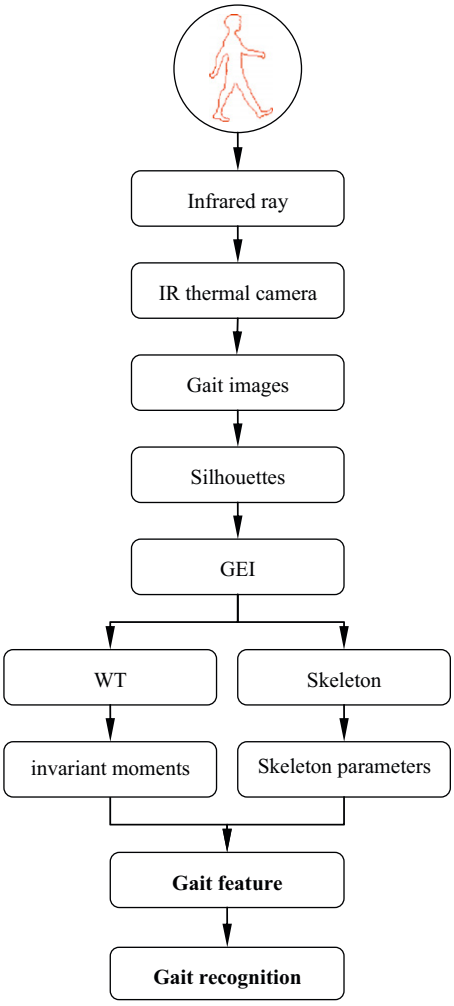


**Fig. 3.** Technical flow chart.

detector which can translate the infrared ray into electrical signal. The signal processing system can generate infrared image. In this way, the infrared gait video can be collected by using this thermal camera. Detection distance can take some impact on the quality of infrared image. The image of whole body cannot be obtained in short-distance between camera and human body. Also the long-distance will influence the image quality. In a set of experiments, thermal camera was about 6 m away from subjects and we established an infrared thermal gait database (ITGD). The temperature sensitivity of A40M is 0.08 °C for 30 °C. Frame frequency is 50/60 HZ and spatial resolution is 1.3 mrad. Gait video was collected indoors and each subject was asked to walk with four conditions (normal walking, holding ball, loading package, wearing heavy coat). The image size is $320 \times 240$ pixels. Fig. 4 gives four images with four conditions. For the recognition performance, there are some important factors including complex background, carrying objects, heavy coat. So we designed these four situations and set static background indoor. However, it is obvious that more factors need to be taken into account in our dataset. This will be our future work for outdoor experiments.

### 2.2. Wavelet decomposition of GEI

(1) *Gait Energy Image*: The gait energy image (GEI) could be obtained by adding normalized silhouettes together. As shown in Fig. 4, the gray-value of body area is different from that of background because of the different temperature between human body and surroundings. So we can set a global threshold to extract body silhouette. The formula follows as

$$I_i(x,y) = \begin{cases} 1 & |P_i(x,y)| > \tau \\ 0 & |P_i(x,y)| \le \tau \end{cases} \quad (1)$$

In Eq. (1), $P_i$ is gray-value in point $(x,y)$ and $\tau$ is the global threshold. Generally, the gray-value of surroundings is 30 below. The body's gray-value is higher than 80. In this paper, we fixed 70 as the global threshold. Thinking of the possibility for the hole, clearance and other noises in silhouettes, the binary image was processed by using morphological erosion and dilation. The formula follows as

$$E(x,y) = \underset{i,j=0}{\overset{m}{AND}}[f(x+i,y+j)\&\mathrm{T(i,j)}] \quad (2)$$

$$D(x,y) = \underset{i,j=0}{\overset{m}{OR}}[f(x+i,y+j)\&\mathrm{T(i,j)}] \quad (3)$$

Eq. (2) is the erosion and Eq. (3) presents the dilation. Here, $f(x,y)$ expresses the binary image and $T(i,j)$ is structure element. The silhouettes were normalized to adjust location and size of binary image. Also its aim was to eliminate errors derived from camera dithering and distance changes between camera and human body. In this paper, silhouettes were zoomed in (or out) to $150 \times 150$ pixels. Finally, the normalized silhouettes were added together to obtain the gait energy image. Fig. 5 shows the procedure of normalization.

(2) *Wavelet Decomposition of GEI*: The aim of wavelet decomposition (WD) was to decompose the energy of GEI according to different directions. The wavelet decomposition made the GEI to many hierarchical images. Then we could get some energy images with different levels and obtain more energy features of human body. In view of this, we decomposed the GEI in our experiments. Fig. 6 shows the experimental result. The S illustrates GEI. The Ai (decomposition order $i=1$ or 2) is approximation of S. The Hi, Vi and Di represent three components separately: horizontal, vertical and Diagonal component. According to Fig. 6, we can find that three components (H1, V1 and D1) have clear outline with energy feature. However, the other three components (H2, V2 and D2) have body information with limited energy. In order to improve computing speed, we decomposed the GEI only in one-layer and used the Haar wavelet in this paper.

### 2.3. Feature extraction

Firstly, the skeleton parameters were extracted by using the simplified model. The skeleton is an important description of topological relation. For the GEI with slender shape, its skeleton should cover important feature of human body. So we simplified GEI to obtain skeleton. Then skeleton parameters were extracted according to anatomy. The basic steps follow as

(1) To extract skeleton of the GEI based on mathematical morphology.
(2) According to body segment properties [16,17], curve fittings were presented for skeleton's trunk and lower limbs as shown in Fig. 7. Its aim of curve fitting was not only to eliminate the influence from motion of upper limbs, but also to cut down some skeleton's branches.
(3) According to the four points A $(x_1, y_1)$, B $(x_2, y_2)$, C $(x_3, y_3)$ and D $(x_4, y_4)$ as shown in Fig. 7, we computed the height of total skeleton: $H = y_1 - \min(y_3, y_4)$. Then we calculated the

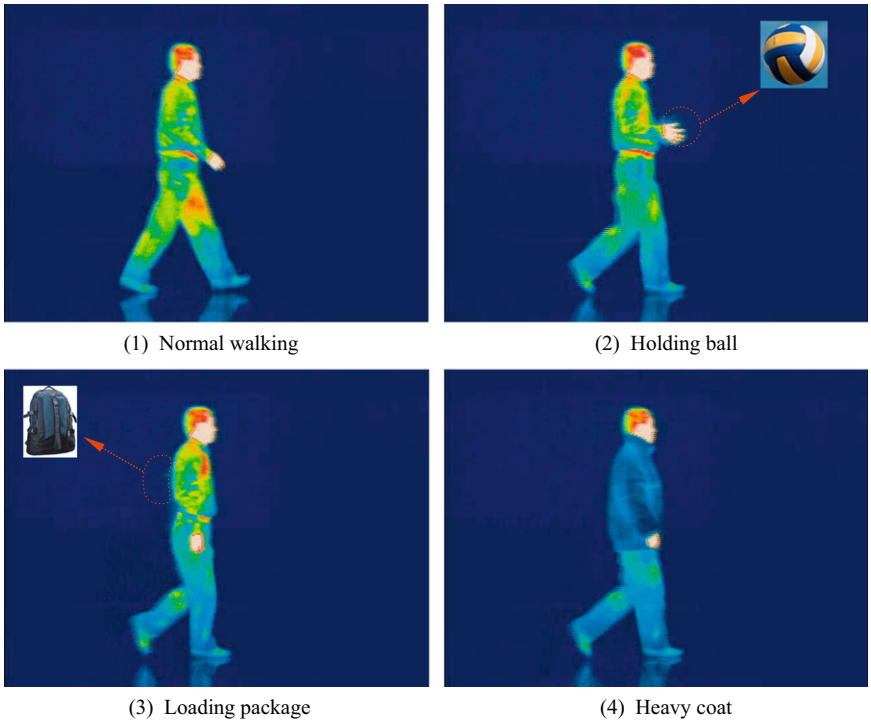


**Fig. 4.** Infrared images with different conditions.

**Fig. 5.** Pretreatment of IR image.

following parameters:

$$P_1 = \frac{\sqrt{(y_1-y_2)^2+(x_1-x_2)^2}}{H} \quad (4)$$

$$P_2 = \frac{\sqrt{(y_2-y_3)^2+(x_2-x_3)^2}}{H} \quad (5)$$

$$P_3 = \frac{\sqrt{(y_2-y_4)^2+(x_2-x_4)^2}}{H} \quad (6)$$

$$\theta_1 = \frac{|x_3-x_2|}{|y_3-y_2|} \quad (7)$$

$$\theta_2 = \frac{|x_4-x_2|}{|y_4-y_2|} \quad (8)$$

Here $P_1$ is proportion between trunk and height of skeleton. In Eqs. (5)–(6), the $P_2$ and $P_3$ illustrate the relations between skeleton height and lower limbs. In Eqs. (7)–(8), $\theta_1$ and $\theta_2$ present the angular information for lower limbs. According to the anatomy, the height of knee joint is $0.285H$ ($H$ is the height of skeleton) above the ground [16,17]. We determined the coordinate of skeleton's point above $0.285H$. Then these points were fitted and the segment AB could be obtained by using least square method as shown in Fig. 7. Also, we draw the line-segment BC and BD using the method of curve fitting. According to skeleton structure, we find that these skeleton parameters based on simplified model should contain some anatomical characters of human body.

Secondly, the invariant moments were extracted by using the integral model. The invariant moments have the invariance of rotation, scaling, translation, gray change and contrast change. So we extracted the invariant moments based on integral model. The steps follow as

(4) To decompose the gait energy image.
(5) To compute moment parameters of approximation (S), horizontal component (H1), vertical component (V1) and diagonal component (D1).
(6) To compute the logarithm for moment parameters because a wide range for the value.
(7) To normalize moment parameters and skeleton parameters respectively.

Using this method, we could obtain 33 parameters (28 parameters based on integral model and 5 parameters based on simplified model). The parameters based on simplified model implied anatomical characteristic. At the same time, the parameters based on integral model covered the behavioral characteristic. In this way, the gait parameters can include the anatomical and behavioral characteristics.

### 2.4. Gait recognition based on SVM

The traditional methods of statistical pattern recognition are based on the groundwork that there are sufficient samples. The performance can be ensured theoretically when the sample number tends to infinite. Theory is nice, but there are limited

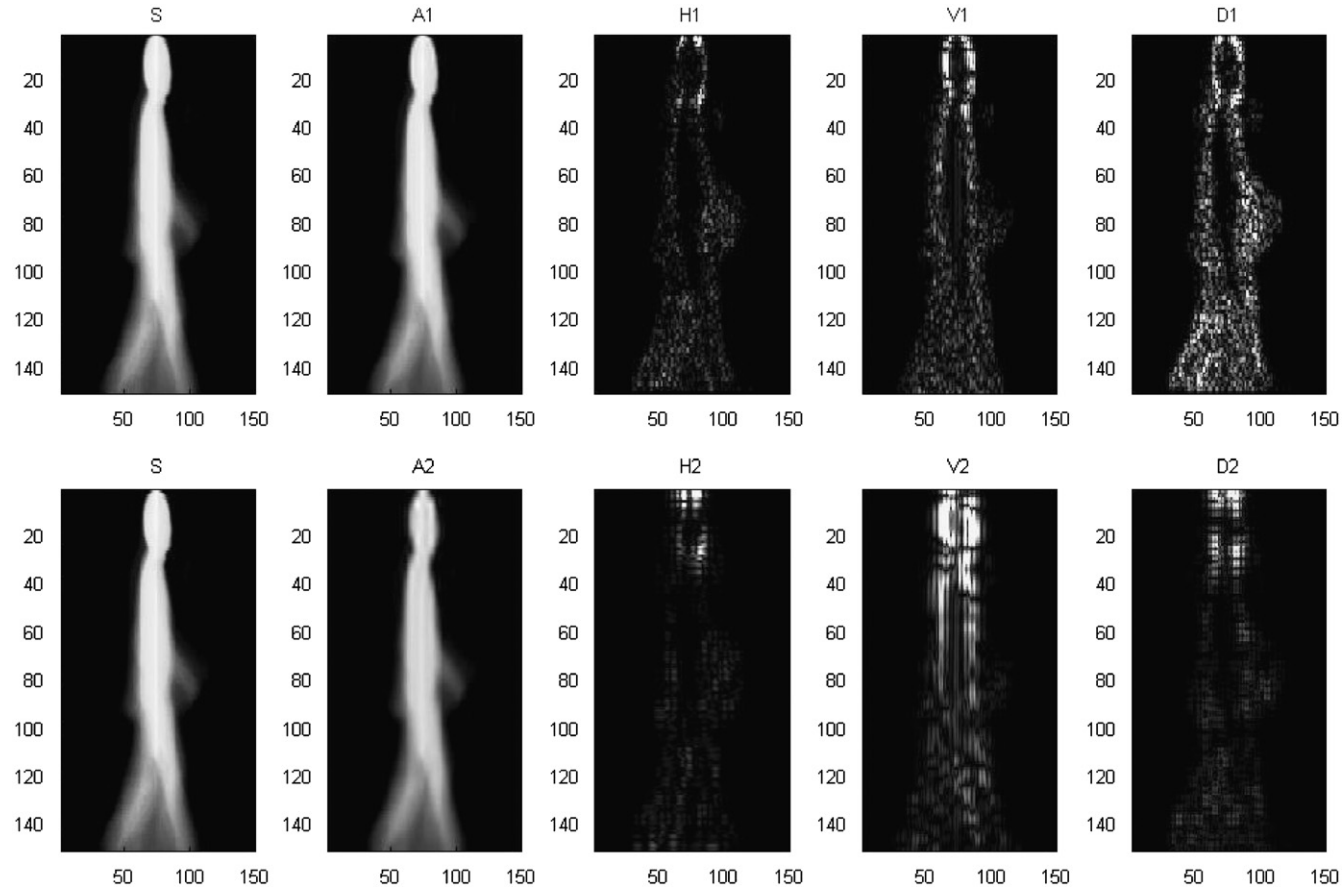


**Fig. 6.** Wavelet decomposition of GEI.

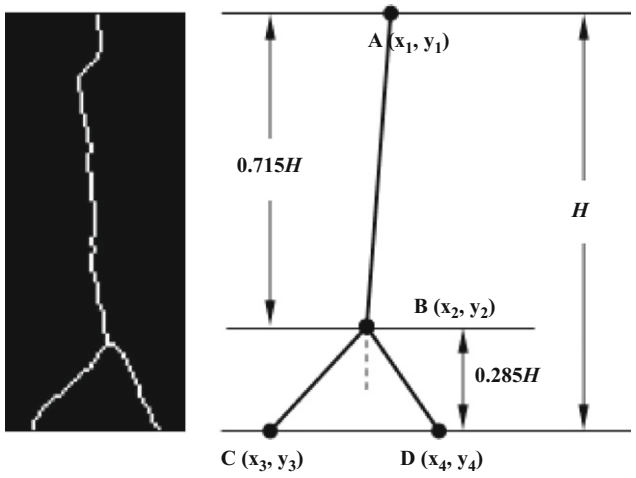


**Fig. 7.** Sketch map of key points.

samples in gait recognition. In this case, it is difficult for some methods to achieve ideal results. However, support vector machine (SVM) is a machine learning method based on small sample statistics theory. This method has some advantages to deal with the pattern recognition involving small sample, non-linear, high-dimension data [18]. So we used SVM to classify gaits.

The SVM is designed for binary classification. But gait recognition is to solve problem with multi-class classification. Here one of the technology difficulties is how to use SVM to classify multi-class gaits. In this paper, we used the method of 'one-to-others' [19]. For $N$-class classification, the number of SVM classifier is $N$. Each classifier labels one-class from the others. The identification result would be decided by maximum distance of output value with the interface $(w \cdot x+b)$. Provided that $m$-class samples $(S_1, S_2,\ldots,S_m)$ need to be classified. Then we designed classifiers: $C_1, C_2,\ldots,C_m$. Each classifier $C_i$ $(i=1,2,\ldots,m)$ was trained by the sample $S_i$ $(i=1,2,\ldots,m)$ which was used as positive class. The other samples $(S_j,\ j\neq i)$ were used as negative sample for training classifier $C_i$. For the positive sample, the output of SVM labeled +1. The system labeled $-1$ for the negative sample. While predicting the recognition performance, we input the sample $T_i$ as testing item. If the result labels +1 for the classifier $C_i$, we would classify the sample $T_i$ to be $i$ class. Else the result would be wrong.

On the side, the kernel is one of most important parameters for SVM. Different kernel faces the different mapping space for testing samples. This paper presents three common kernels: Linear kernel, Polynomial kernel and radial basis function (RBF) kernel.

$$\text{(I) Linear kernel,}\quad K(x,x_i)=x\cdot x_i \tag{9}$$

$$\text{(II) Polynomial kernal,}\quad K(x,x_i)=[(x\cdot x_i+1)]^q \tag{10}$$

$$\text{(III) Radial basis function kernel :}\quad K(x,x_i)=\exp\{-|x-x_i|^2/2\sigma^2\} \tag{11}$$

For the infrared gait video, each subject have four sequences. In experiments, we chose three sequences as training items and the other one sequence as testing item.

**Table 1**
Comparision with ANN and SVM.

| Exp. | Training item | Testing item | Parameters | ANN | | | SVM | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Linear (%) | RBF (%) | BP (%) | Linear (%) | Cubic polynomial (%) | RBF (%) |
| A | Normal walking<br>With volleyball<br>With package | Heavy coat | Skeleton | 26 | 30 | 35 | 30 | 39 | 43 |
| B | Normal walking<br>With volleyball<br>With package | Heavy coat | Invariant moments | 39 | 43 | 48 | 43 | 52 | 57 |
| C | Normal walking<br>With volleyball<br>With package | Heavy coat | Skeleton+Invariant moments | 57 | 70 | 74 | 65 | 74 | 78 |

**Table 2**
Results of recognition by using SVM.

| Exp. | Training item | Testing item | Conventional image (%) | IR image (%) |
|---|---|---|---|---|
| 1 | With volleyball, With package, Heavy coat | Normal walking | 83 | 91 |
| 2 | Normal walking, With package, Heavy coat | With volleyball | 74 | 83 |
| 3 | Normal walking, With volleyball, Heavy coat | With package | 74 | 87 |
| 4 | Normal walking, With volleyball, With package | Heavy coat | 70 | 78 |

## 3. Results and discussion

This method was applied to infrared thermal gait database. There were 23 subjects (13 males and 10 females). Their age was from 19 years to 30 years. Each subject was asked to walk with four conditions: normal walking, loading package of known weight (5 kg), holding volleyball and wearing heavy coat. There are as many as four video sequences for each subject: (normal walking) $\times$ (loading package) $\times$ (holding volleyball) $\times$ (wearing heavy coat). So there are 92 ($23 \times 4$) sequences in this infrared database. In order to estimate the performance of gait recognition, we used probability of correct recognition (PCR) as the guideline. While testing the recognition performance, the sample $T_i$ would be put into the classifiers. If the input $T_i$ had the result $i$, it was confirmed that the output was right. If the sample $T_i$ had the result $j$ ($i \neq j$), the output was wrong. The PCR was shown as following:

$$PCR = N_r/N \times 100\% \tag{12}$$

In Eq. (12), PCR is the probability of correct recognition. $N_r$ is the number of samples that was classified right and $N$ is the number of total subjects.

Table 1 gives comparative results of recognition performance for the single model and double model. As presented in Table 1, the PCR was lower than 50% when we only used the skeleton parameters. When the moment parameters were used to classify gaits, the PCR was lower than 60%. If double model (integral model+simplified model) was used to extract gait features, we could achieve more ideal results. According to the test results from Table 1, it was proved that this method with double model was beneficial to classify gaits. At the same time, this paper presents recognition results by using artificial neural network (ANN) with three networks: linear, radial basis function (RBF) and back-propagation (BP) as presented in Table 1. The accurate rate of the recognition reached 74% when using ANN with BP network as classifier. However, SVM could identify the class feature better. So we used SVM to recognize infrared gaits in this paper. In addition, The PCR was lower when we used SVM with linear kernel and PCR was improved when the polynomial kernel was used. An ideal result was achieved when using SVM with RBF kernel in experiment. For this reason, the RBF kernel was used for identification.

Table 2 gives recognition results by using SVM with RBF kernel for two types of video. There are 23 subjects who were not common between the IR video and the conventional video. For conventional video, each subject was also asked to walk with four conditions: normal walking, loading package of known weight (5 kg), holding volleyball and wearing heavy coat. We detected silhouettes by using background subtraction. At the same time, the GEI was obtained by adding normalized body silhouettes together. The same methods were used to extract gait features for conventional video. The recognition rate was 70%–83%. The PCR was lower than that of IR video. When we trained SVM with three items (with volleyball, with package, heavy coat) and tested the other one for IR video, the PCR was 91%. The lowest recognition rate was 78% when we used the sequence with heavy coat as testing sample. For testing items of holding objects (with package and with volleyball), the PCR was 87% and 83%, respectively. In addition, Ref. [6] performed four experiments on infrared night gait dataset. The results showed that carrying a bag had much more impact on the recognition performance. The recognition rate was 60% when subjects carried a bag in Ref. [6]. In this paper, the recognition rate was 87% when subjects walked with a package. The PCR was insensitive for the items of holding ball and loading package. However, there was significant influence for the item of wearing heavy coat. As expected, the gait-related factors include the body silhouette. When subject walks normally, the silhouette will be close to his/her body structure. When subject walks with a heavy coat, the outline will be changed. This will make a larger error between silhouette and human body. So heavy coat affects the feature extraction based on GEI. This impact leads to a lower recognition rate as presented in Table 2.

## 4. Conclusions

Human body is a natural emitter of infrared ray and the temperature is not similar to that of surroundings. So the infrared image is not easy to be disturbed by complex background and illumination variations. Also IR imagery appears more robust for silhouette extraction. In view of this, we used infrared thermal camera to collect gait video and established an infrared thermal gait database. To test the recognition performance, we used double-model

to extract gait features and achieved 78%–91% for the probability of correct recognition. From our study, the infrared thermal image is beneficial to detect body silhouette in gait recognition. Also the recognition rate is insensitive for the objects (such as package and ball). This method is robust against noises form background, illumination and walking speed. However, there is significant influence on gait recognition when subject wears heavy coat. Our future work will take into account more factors, such as subject number, view and time. In addition, fusion of dual infrared information will be explored to recognize people by their gaits.

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## References

[1] S. Prabhakar, S. Pankanti, A.K. Jain, Biometric recognition: security and privacy concerns, IEEE Security & Privacy (2003) 33–42.
[2] K. Delac, M. Grgic. A survey of biometric recognition methods, in: 46th International Symposium Electronics in Marine, 2004, pp. 184–193.
[3] A.K. Jain, Technology: biometric recognition, Nature 449 (6) (2007) 38–40.
[4] M.S. Nixon, J.N. Carter, Advances in automatic gait recognition, in: Proceedings of Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2004, pp. 139–144.
[5] L. Lee, W.E.L. Grimson, Gait analysis for recognition and classification, in: Proceedings of the Fifth IEEE Conference on Automatic Face and Gesture Recognition, Washington, DC, 2002, pp. 148–155.
[6] D. Tan, K. Huang, S. Yu, et al., Efficient night gait recognition based on template matching. in: Proceedings of the 18th International Conference on Pattern Recognition, 2006, pp. 1000–1003.
[7] B. Bhanu, J. Han, Kinematic-based human motion analysis in infrared sequences [A], in: Proceedings of Sixth IEEE Workshop on Applications of Computer Vision[C], Orlando, Florida, United States, 2002, pp. 208–212.
[8] J. Han, B. Bhanu, Human activity recognition in thermal infrared imagery, in: Proceedings of the IEEE Workshop on Object Tracking and Classification Beyond the Visible Spectrum, 2005.
[9] Z. Xue, F. Zhang, D. Ming, et al., Gait recognition based on body silhouette area feature, Computer Engineering 34 (1) (2008) 195–197.
[10] R.T. Collins, P. Cross, J. Shi, Silhouette-based human identification from body shape and gait [A], in: Proceedings of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition[C], Washington, DC, USA, 2002, pp. 351–356.
[11] S. Sarkar, P.J. Phillips, Z. Liu, et al., The human ID gait challenge problem: data sets, performance, and analysis, IEEE Transactions on Pattern Analysis and Machine Intelligence 27 (2) (2005) 162–165.
[12] J. Han, B. Bhanu, Statistical feature fusion for gait-based human recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, vol. 2, 2004, pp. 842–847.
[13] A. Veeraraghavan, A.R. Chowdhury, R. Chellappa, Role of shape and kinematics in human movement analysis. in: Proceedings of the IEEE Conference on Computer Vision Pattern Recognition, Washington, DC, June 2004.
[14] G.V. Veres, L. Gordon, J.N. Carter, et al., What image information is important in silhouette-based gait recognition? IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'04) 2 (2004) 776–782.
[15] Z. Liu, S. Sarkar, Improved gait recognition by gait dynamics normalization, IEEE Transactions on Pattern Analysis and Machine Intelligence 28 (6) (2006) 863–876.
[16] D.A. Winter, The Biomechanics and Motor Control of Human Movement, second ed, John Wiley and Son, New Jersey, USA, 1990.
[17] J.-H. Yoo, M.S. Nixon, C.J. Harris, Extracting human gait signatures by body segment properties [A], in: Proceedings of the IEEE Southwest Symposium on Image Analysis and Interpretation [C], University of Southampton, Southampton, UK, 2002.
[18] B. Wan, R. Wang, X. Zhu, et al., Principles of SVM and its application in microcalcifications detection in mammogram, Acta Electronica Sinica 32 (4) (2004) 587–590.
[19] C.-C. Chang, C.-J. Lin, LIBSVM: a library for support vector machines, 2001. Software available at 〈http://www.csie.ntu.edu.tw/∼cjlin/libsvm〉.

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